Symmetric Pattern Based Word Embeddings for Improved Word Similarity Prediction

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CoNLL 2015

Apples and Oranges

fruits

sweet

juicy

round

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Apples $\boxed{\text{and}}$ Oranges

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X $\boxed{\text{and}}$ Y

fruits

sweet

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X and Y

Symmetric Patterns

Overview

- **The problem**
  - *Word embeddings do not capture pure word **similarity***
- **The Solution**
  - ***symmetric patterns**-based word embeddings*
  - *First embeddings to support for **antonyms** (e.g., good/bad) w/o using a dictionary*
- **Results**
  - ***5.5%** improvement over six state-of-the-art models*
  - ***10%** improvement with a **joint** model*
  - ***20%** improvement on **verbs***

Word Similarity

- Whether two words are **semantically** similar
  - cats are similar to dogs

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- Human judgment evaluation

Vector Space Models

DS Hypothesis (Harris, 1954)

... tokens to date, **friend** lists and recent ...

... by my dear **friend** and companion, Fritz von ...

... even have a **friend** who never fails ...

... by my worthy **friend** Doctor Haygarth of ...

... and as a **friend** pointed out to ...

... partner, in-laws, relatives or **friends** speak a different ...

... petition to a **friend** Go to the ...

... otherwise, to a **friend** or family member ...

...images from my **friend** Rory though - ...

... great, and a **friend** as well as a colleague, who, ...

...

Examples taken from the ukwac corpus (Baroni et al., 2009)

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Vector Space Models

$$\begin{pmatrix} 0 \\ 0.5 \\ 0.76 \\ -0.12 \\ 0.76 \\ 0 \\ 0 \\ -0.51 \\ . \\ . \\ . \end{pmatrix}$$

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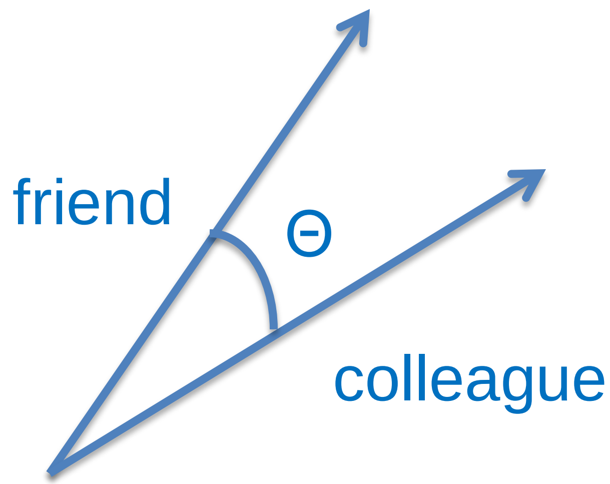

Similarity or Relatedness?

Hill et al., 2014

cup coffee

Similarity or Relatedness?

Hill et al., 2014

sugar

milk

cup

coffee

tea

hot_water

cookie

Similarity or **Dis**similarity?

tall **short**

Similarity or Dissimilarity?

cm

feet

tall

short

John

is

length

*Current Vector Space Models do not Capture (**pure**) Word **Similarity***

Symmetric Patterns Contexts

Davidov and Rappoport, 2006

from **X** to **Y**

X and **Y**

X or **Y**

neither **X** nor **Y**

X as well as **Y**

Symmetric Patterns Contexts

Davidov and Rappoport, 2006

bright and **shiny**

shiny and **bright**

Symmetric Patterns (SPs)

- Words that co-occur in SPs tend to be semantically **similar**
  - Widdows and Dorow, 2002
  - Davidov and Rappoport, 2006
  - Kozareva et al., 2008
  - Feng et al., 2013
  - **Schwartz** et al., 2014

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John *and* Mike

neither here *nor* there

bold *and* beautiful

Paris *or* Rome

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neither here *nor* there

#car *or* wheel

John *and* Mike

#*neither* cup *nor* coffee

bold *and* beautiful

Paris *or* Rome

#dog *and* leash

SP-based Word Embeddings

$$V^{sp}_{\mathbf{dog}} = \begin{pmatrix} \text{PPMI(dog,house)} \\ \text{PPMI(dog,mouse)} \\ \text{PPMI(dog,zebra)} \\ \text{PPMI(dog,wine)} \\ \text{PPMI(dog,cat)} \\ \text{PPMI(dog,dolphin)} \\ \text{PPMI(dog,bottle)} \\ \text{PPMI(dog,pen)} \\ . \\ . \\ . \end{pmatrix}$$

* Simple smoothing applied

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✓ **similarity rather than relatedness**

* Simple smoothing applied

Antonyms

big / small

- Some SPs are indicative of antonymy (Lin et al., 2003)
  - “*either* X *or* Y” (*either* big *or* small)
  - “*from* X *to* Y” (*from* poverty *to* richness)

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See Paper for Details!

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Word Embeddings that Identify Antonyms

ACL 2015 Papers

- *Revisiting Word Embedding for Contrasting Meaning* (Chen et al.)
- *Learning Semantic Word Embeddings based on Ordinal Knowledge Constraints* (Liu et al.)
- *AutoExtend: Extending Word Embeddings to Embeddings for Synsets and Lexemes* (Rothe and Schutze, **Best paper award**)

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First model to support for antonyms without using a dictionary or a thesaurus!

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✓ **similarity rather than relatedness**

✓ **support for antonyms**

* Simple smoothing applied

Experiments

- Embeddings are generated using an 8G words corpus

- Baselines: six state-of-the-art models

- Word similarity task
  - SimLex999 dataset (Hill et al., 2014)

Results

Model	Spearman's ρ
Glove (Pennington et al., 2014)	0.35
PPMI-Bag-of-words	0.423
word2vec CBOW (Mikolov et al,. 2013)	0.43
Dep (Levy and Goldberg, 2014)	0.436
NNSE (Murphy et al., 2012)	0.455
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$$f_{joint}(w_i, w_j) = \alpha \cdot f_{SP}(w_i, w_j) + (1-\alpha) \cdot f_{skip-gram}(w_i, w_j)$$

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POS Analysis

Model	Adj.
Glove (Pennington et al., 2014)	0.571
PPMI-Bag-of-words	0.548
word2vec CBOW (Mikolov et al,. 2013)	0.579
Dep (Levy and Goldberg, 2014)	0.54
NNSE (Murphy et al., 2012)	0.594
word2vec skip-gram (Mikolov et al,. 2013)	0.604
SP	**0.663**

POS Analysis

Model	Adj.	Nouns
Glove (Pennington et al., 2014)	0.571	0.377
PPMI-Bag-of-words	0.548	0.451
word2vec CBOW (Mikolov et al,. 2013)	0.579	0.48
Dep (Levy and Goldberg, 2014)	0.54	0.449
NNSE (Murphy et al., 2012)	0.594	0.487
word2vec skip-gram (Mikolov et al,. 2013)	0.604	**0.501**
SP	**0.663**	0.497

POS Analysis

Model	Adj.	Nouns	Verbs
Glove (Pennington et al., 2014)	0.571	0.377	0.163
PPMI-Bag-of-words	0.548	0.451	0.276
word2vec CBOW (Mikolov et al,. 2013)	0.579	0.48	0.252
Dep (Levy and Goldberg, 2014)	0.54	0.449	0.376
NNSE (Murphy et al., 2012)	0.594	0.487	0.318
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More Results

- List of SPs is acquired automatically (**not manually defined**)
- Antonymy as Word Analogy
- Wordsim353 experiments
- And more…

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- Antonymy as Word Analogy
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See Paper!

Summary

- Word embeddings based on symmetric patterns
  - They capture **similarity** and not **relatedness**
  - The first word embeddings model to mark **antonym** pairs as dissimilar (w/o using a dictionary)

- Experiments on SimLex999
  - ***5.5%*** *improvement over six state-of-the-art models*
  - ***10%*** *improvement with a* ***joint*** *model*
  - ***20%*** *improvement on* ***verbs***

Future Work

- Enhancing bag-of-words models with SPs
- Does order count? **asymmetric** symmetric patterns

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ww.cs.huji.ac.il/~roys02/papers/sp_embeddings/sp_embeddings.html